



UNIVERSITY OF  
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# Longitudinal Analysis and the Potential For Causal Interpretations

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*Directions for Improving ILSA Design and Analysis*  
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## Causal inference in ILSA

- The educational systems investigated in ILSA are embedded in countries with different cultures, languages, economies and historical backgrounds
- The heterogeneity among the countries makes it difficult to make correct causal inferences about determinants of achievement from cross-sectional data
- An alternative approach may be to use within-country change over time to identify causal relations between determinants and educational outcomes



## Threats to valid causal inference in cross-sectional data

- "Correlation is not causation"
- *Omitted variables*. If the analytical model incorrectly leaves out one or more important variables, estimates of the effects of the included variables will be biased
- *Reverse causation*. If the assumed independent variable is affected by the assumed dependent variable, or if there is a bidirectional relation, causal inference will be incorrect
- *Errors of measurement*. Random errors in observed variables typically cause relations to be underestimated, causing biased inferences



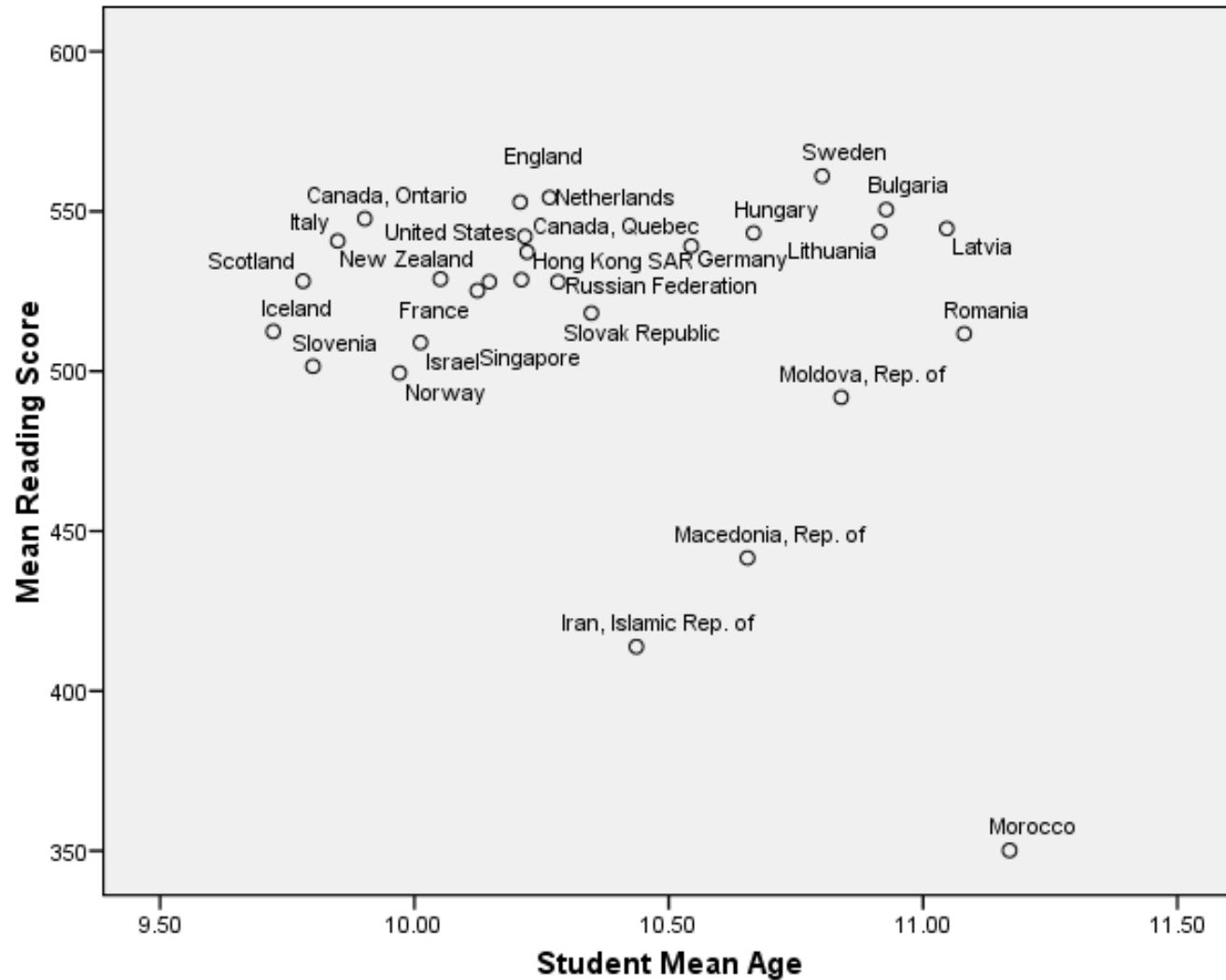
## The longitudinal approach with aggregated data

- Aggregated ILSA data is longitudinal at country level in studies with trend design (e.g., PIRLS, TIMSS and PISA)
- With longitudinal data, countries can be their own controls, thereby removing bias from omitted variables which are fixed characteristics of the countries.
- Mechanisms which generate reverse causation do not operate at country level
- Aggregated data typically is more reliable than micro data



# Mean age and mean reading achievement in PIRLS 2001

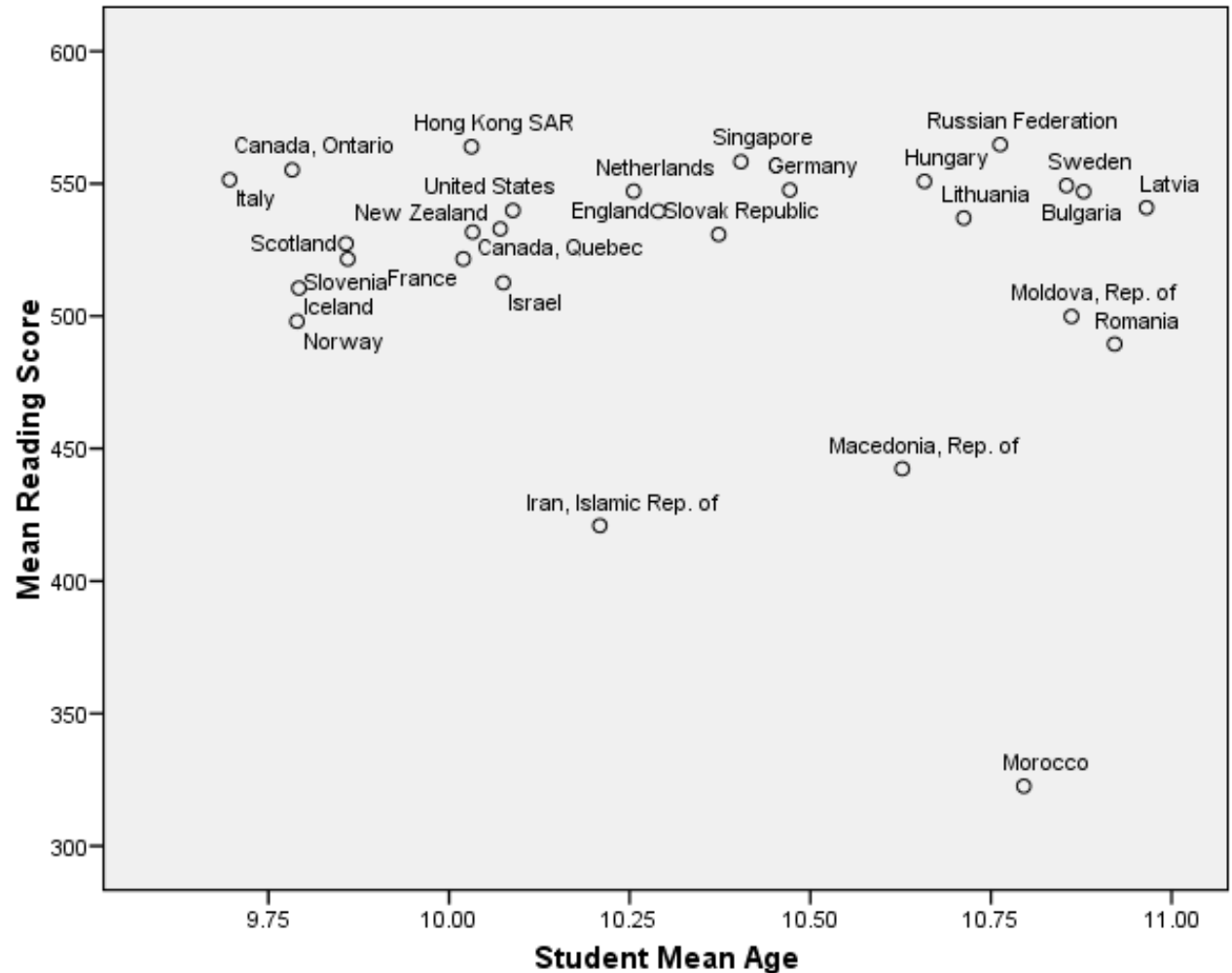
The correlation between mean student age and reading achievement is  $-.23$ .





## Mean age and mean reading achievement in PIRLS 2006

The correlation between mean student age and reading achievement is  $-.15$ .



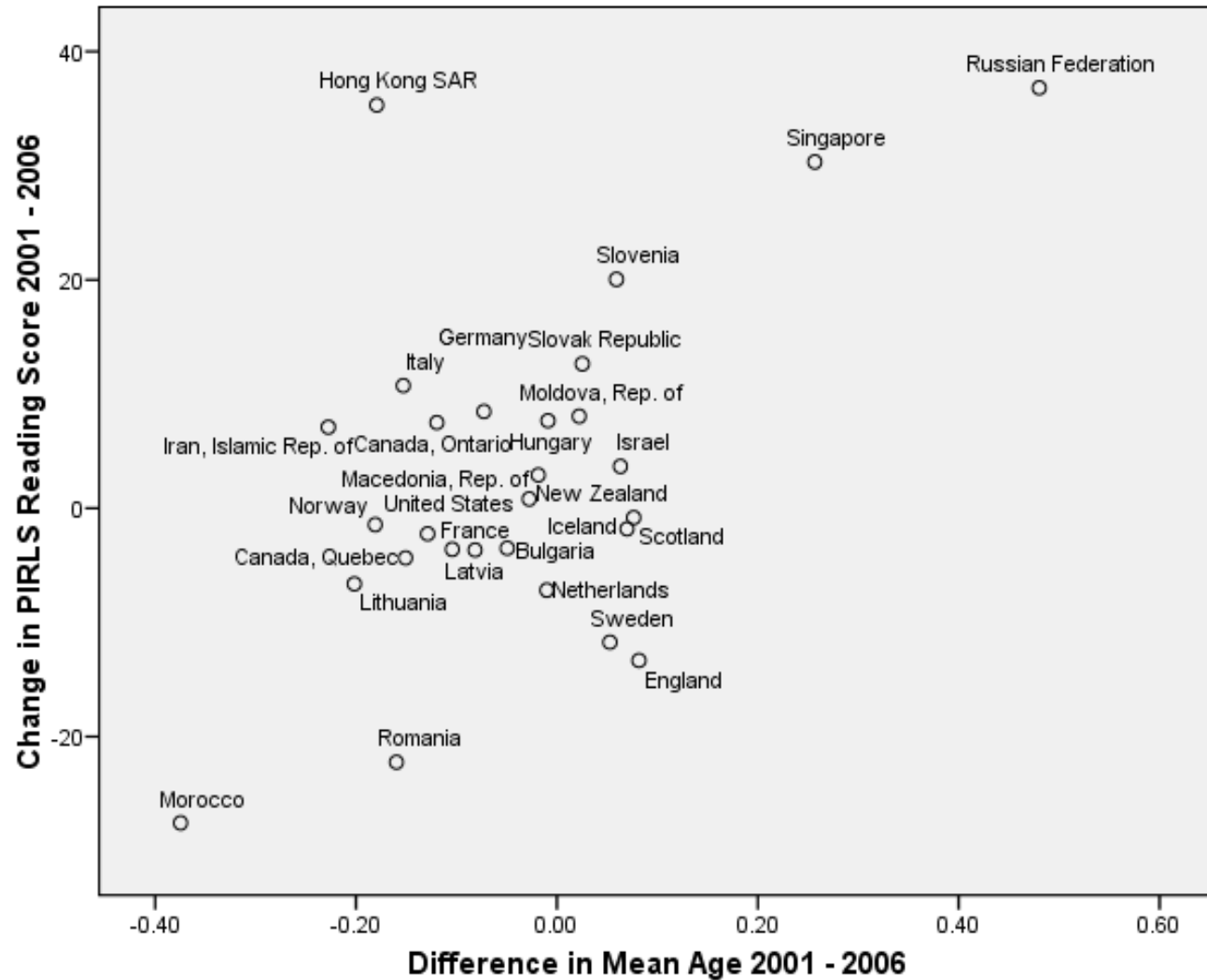


# Difference in age and difference in reading achievement PIRLS 2001 and 2006

Strong correlation  
between difference in  
mean age and difference  
in reading score ( $r = .53$ ).

$b = 45$

The  $b$  coefficient  
estimates the effect of an  
additional year of  
schooling and an  
additional year of age.





Gustafsson, J. E. (2013). Causal inference in educational effectiveness research: a comparison of three methods to investigate effects of homework on student achievement. *School Effectiveness and School Improvement*, 24(3), 275-295.

- Research on relations between amount of homework and student achievement has given inconclusive results:
  - Positive correlations have been found in some studies, and particularly so with older students (high school or junior high school)
  - Negative correlations have been found in other studies, and particularly so with primary school students
- It may be suspected that many of these studies suffer from biased inference due to reverse causation, omitted variables and errors of measurement





## Data

- Data from 22 countries participating in TIMSS 2003 and TIMSS 2007 with grade 8 students.
- Student estimates of number of minutes of homework per week (StuTime03 and StuTime07)
- Teacher estimates of number of minutes of assigned homework per week (TeachTime03 and TeachTime07)
- Mathematics achievement, PV1



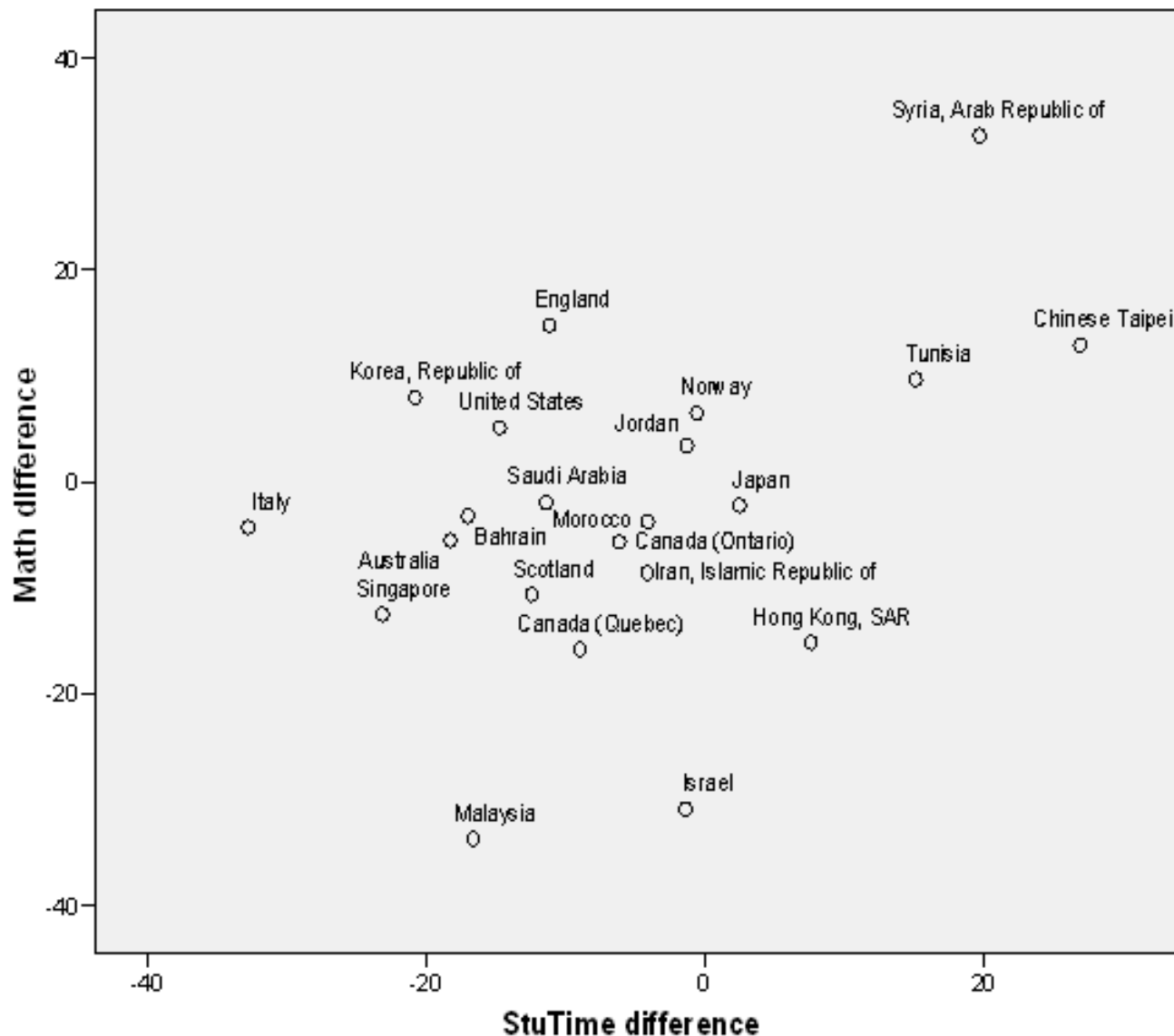
Country	TIMSS 2003					TIMSS 2007				
	N	Math	StuTime	TeachTime	Nbooks	N	Math	StuTime	TeachTime	Nbooks
Australia	4436	502	84	61	3.63	4019	496	66	49	3.34
Bahrain	4199	402	97	78	3.00	4198	398	80	41	2.74
Canada (Ontario)	4215	521	110	98	3.50	3448	517	106	76	3.35
Canada (Quebec)	4411	542	105	82	2.89	3956	527	96	74	2.75
Chinese Taipei	5379	584	75	74	2.86	4046	597	102	82	2.94
England	2787	499	49	51	3.24	4004	513	38	41	3.02
Hong Kong, SAR	4972	585	108	73	2.42	3412	570	115	87	2.48
Iran, Islamic Republic of	4942	412	101	142	2.10	3981	403	97	122	2.00
Israel	3948	495	122	122	3.36	3172	464	121	119	3.24
Italy	4249	483	181	143	2.98	4408	479	148	143	3.17
Japan	4856	569	38	33	3.02	3222	567	40	41	3.01
Jordan	4489	424	116	91	2.46	5251	427	115	68	2.58
Korea, Republic of	5232	587	57	40	3.19	4183	595	36	44	3.47
Malaysia	5314	508	142	129	2.45	4466	474	125	103	2.44
Morocco	2943	387	138	120	2.10	3044	382	132	79	2.32
Norway	4133	462	105	84	3.52	4506	468	104	101	3.39
Saudi Arabia	4295	333	86	69	2.50	4225	331	75	35	2.39
Scotland	3386	499	60	46	2.98	3928	488	47	44	2.75
Singapore	6018	605	137	122	2.96	4493	592	114	99	2.86
Syria, Arab Republic of	3760	363	133	105	2.34	4530	396	153	91	2.24
Tunisia	4931	411	142	82	2.22	4080	421	157	101	2.10
United States	8912	504	121	93	3.21	7117	509	106	85	2.97

Country level:  $r(\text{StuTime03}, \text{TeachTime03}) = .85$ ;  $r(\text{StuTime03}, \text{StuTime07}) = .92$ ;  
 Student level (mean):  $r(\text{StuTime03}, \text{TeachTime03}) = .15$ , range .00 - .37



## Results from the difference-in- differences analysis

The unstandardized  
regression coefficient  
of Math difference on  
the StuTime  
difference was .42  
( $t = 1.99$ ,  $p < .06$ ).





## Issues in estimation and modeling

- The simple difference-in-differences analysis of aggregated two-wave data used here is limited in scope, flexibility and power.
- Regression analysis of micro-data with fixed country effects, cross-product terms, and cluster-robust standard errors brings multiple advantages, e.g.:
  - Interactions at the country level (e.g., Hanushek, Link, & Woessmann, L., 2013).
  - Interactions with individual characteristics (e.g., Rosén & Gustafsson, 2016)
  - Controls for time-varying characteristics (e.g., Hanushek, Link, & Woessmann, L., 2013).



## Issues in estimation and modeling, cont

- Bollen and Brand (2008) proposed a structural equation modeling (SEM) approach to analysis of panel data.
- Such an approach may bring multiple advantages:
  - Statistical tests of the appropriateness of different model assumptions
  - Constraints on model parameters
  - Use of latent variables
  - Multiple-group models



Gustafsson, J.-E., & Nilsen, T. (2016). The Impact of School Climate and Teacher Quality on Mathematics Achievement: A Difference-in-Differences Approach. In Nilsen, T. & Gustafsson, J.-E. (Eds.) *Teacher quality, instructional quality and student outcome. Relationships across countries, cohorts and time*. Berlin: Springer.

- School emphasis on academic success (SEAS) is an aspect of school climate which in numerous studies has been shown to correlate with achievement.
- Is the correlation due to a causal relation?

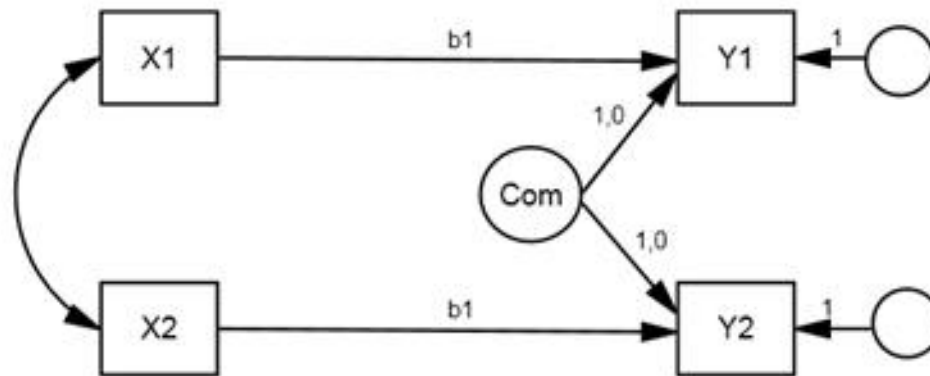


## Data

- All countries (N = 38) that participated in TIMSS 2007 and TIMSS 2011 with grade 8 students.
- Five items to measure SEAS: (1) teachers' understanding of and (2) success in implementing the school's curriculum, (3) teachers' expectations for student achievement, (4) parental support for student achievement, and (5) students' desire to do well in school
- Mathematics achievement, 5 plausible values
- All variables aggregated to country level



## SEM implementation of panel model for two time points



Outcome  $Y_1$  is regressed on predictor  $X_1$  at timepoint 1. Similarly, outcome  $Y_2$  is regressed on predictor  $X_2$  at timepoint 2. This produces two regression coefficients that are constrained to be equal ( $b_1$ ).  $Com$  is a latent variable that captures the effect of the fixed characteristics at the two time points.





## Goodness-of-fit statistics and effect estimates

Model	Random effects			
	Chi-square	Df	Effect	t-value
<i>SEAS</i>				
1 latent, 5 observed	201.78*	58	0.31	2.83*
Teacher's understanding	8.71*	3	-0.02	-0.28
Teacher's implementation	11.16*	3	-0.04	-0.45
Teacher's expectations	6.16	3	-0.05	-0.72
Parental support	1.09	3	0.48	4.82*
Students' desire to learn	9.48*	3	0.13	2.34*



## Conclusions

- SEAS is multidimensional, measuring both aspects of the school and the home
- It seems to be characteristics of the home rather than of the school that influence achievement



## Concluding remarks

- The increasing number of educational systems regularly participating in ILSA with trend design provides a rapidly growing empirical foundation for using country-level longitudinal approaches
- Along with improvements in analytical methodology, this may bring about better possibilities for making causal inferences from ILSA



## References

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- Rosén, M., & Gustafsson, J. E. (2016). Is computer availability at home causally related to reading achievement in grade 4? A longitudinal difference in differences approach to IEA data from 1991 to 2006. *Large-scale Assessments in Education*, 4(1), 1-19.